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(6) RECURSIVE REGION EXTRACTION,

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ABSTRACT

The concept of convergent evidence can be used to accept or reject object regions proposed by slicing. A recursive region extraction scheme similar to that of Ohlander can then be devised which rejects noise well and does not rely as strongly on the independence of multiple features.

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1. Introduction

Image segmentation methods which rely on clustering of evidence from a single source generally suffer from an inability to reject noise responses. Often simple heuristics, based on size or thinness, are used to delete noise points/regions. The difficulty in that approach is that there exists no interaction between the region proposal and noise cleaning phases.

The work of Ohlander [1] is an attempt to overcome the inherent uncertainty in dealing with a single sensor. By starting with high quality color images, additional useful images can be generated through grayscale as well as other local transformations. Histograms are then computed for each of the images. At any stage in the remainder of Ohlander's algorithm, a slice range, selected from the histogram with the most reliable (image) partitioning, is used to extract candidate (object) regions. Candidates are then filtered via simple noise cleaning techniques. The remaining regions, now classified as objects, are removed from all images. Histograms are recomputed and the process is repeated until no more objects can be extracted.

The success of Ohlander's approach depends on the differential homogeneity of regions with respect to the computed features. The misclassification rate is controlled by constructing a wider range of signal sources and by choosing the source with the (current) best signal-to-noise ratio. None-

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theless, the objection stated earlier still applies, since the rejection or merging of regions is done "blindly".

In what follows, an approach is described which applies several sources of information to the same image region. Coincident responses serve to verify the presence of an object region. The goal is to reduce the error rate associated with object acceptance and the computational cost involved in maintaining multiple images and corresponding histograms.

2. Region Extraction Using Convergent Evidence

The use of convergent evidence for slice range selection is discussed in [2]. Briefly, slice ranges for an image are predicted by the existence of clusters in a 2-dimensional histogram of values obtained from thinned edge points. The axes of the histogram correspond to edge value and gray level value. This approach can be extended to choose a best (most reliable) slice range from 2-D histograms derived from color or transform images; however, the present work considers only single images and standard 1-dimensional histograms.

Region extraction using convergent evidence has been described in [3] in the context of the Superslice algorithm. A more extensive paper is in preparation. Superslice relies on the heuristic that object regions are distinct from background in that they contrast with their surroundings at a well-defined border. Coincidence of high contrast and high edge value at the border exemplifies the convergence of evidence supporting the assertion of the object region. The "definedness" of the border may be evaluated as the percentage of border points which coincide with thinned edges (locally maximum edge responses). Thus a match score of 50% means that half the border points are accounted for as lying on edges. In addition, although not used here, one can demand that the matched points represent the shape of the object region. This last notion, called "conformity", is described in [4].

In the present application, the following steps, associated with the Superslice algorithm, are used:

1. Smooth the image, if necessary, to promote cleaner thresholding.
2. Extract a thinned edge picture, e.g, by taking differences of averages at each point in each of several directions and by applying local non-maximum suppression.
3. Determine a slice range and create a binary image by mapping into value 1 those points whose gray levels lie within the slice range; into 0 otherwise.
4. Label all connected components of 1's.
   For each connected region:
   a. Compute its size or area.
   b. Compute the percentage of border points which coincide with thinned edge points.
   c. Compute the average contrast across the border of the region.
   d) Classify the candidate region as object/non-object based on size, edge-match, and contrast.

3. Hyperslice - An Algorithm for Recursive Region Extraction

The algorithm (Hyperslice) described here is an amalgam embodying the control structure of the Ohlander method and the object extraction techniques of Superslice. Hyperslice consists of the following steps:

1. Preprocessing - image smoothing, thinned edge map extraction.
2. Initialize the extracted region mask (ERM) to the empty mask. Initialize the available points mask (APM) to the entire image.
3. Compute histograms for all feature images based on the APM.
4. Determine a "best" slice range over all current histograms and slice the corresponding image.
5. Generate submasks for regions satisfying the Superslice criteria. Add them to the ERM; delete them from the APM.
6. Apply algorithm steps 3-5 recursively to the background set (APM). The algorithm should also be applied recursively to each submask added to the ERM, since the extracted region may be a union of regions discriminable by some other feature.

Several comments are in order. First, the slice ranges chosen for Hyperslice should be rather liberal (i.e., extending beyond valley bottoms in the histogram), since points not

corresponding to well-defined regions will be returned to the APM. The resulting histograms appear more natural (not "carved-out") for this reason. Secondly, the resulting decomposition is order-dependent, i.e., different results may be obtained if the order of selection of slice ranges is changed. If two adjacent regions in the image contribute adjacent peaks in the histogram, then points in the intersection of the overlapping slice ranges will generally belong to the shared edge region. Whichever region is sliced first will tend to accrete more of these points. Since these points lie at or near the true edge, they tend to increase the edge match criterion for that region. Once they are removed from the APM, they are not available to the adjacent region. Consequently, the edge match criterion of the adjacent region may suffer. This is most likely to occur for adjacent regions which lack a strong common border. The 2-dimensional histogram approach in [2] can detect adjacency along weak borders. In practice, the edge match criterion is relaxed somewhat from demanding actual coincidence to allowing proximity (e.g., a region border point adjacent to a thinned edge point is counted as a match).

4. Experiments

The Hyperslice algorithm has been implemented as an interactive system of programs. Several examples illustrate its ability to segment images based on gray level alone (i.e., no other features were used to aid the segmentation). Figure 1 depicts a window of an ERTS frame of the Monterey area in California. The water area contrasts sharply with land mass and very little noise is extracted and subsequently returned to the APM. The subsequent slices extract light and dark fields which contrast with the undifferentiated background region.

The second example is derived from Ohlander's house scene. The average of the three color bands provides the gray-scale. The resulting image has been smoothed by 3x3 median filtering. The first slice range extracts the sky regions and the bright crown of a bush. Next the shadow regions appear along with the bushes. The somewhat darker grass is extracted in the third slice range. Finally the brick is extracted.

The importance of order in the slice range sequence is illustrated in Figure 3. If the brick is extracted before the grass, large portions of grass region accrue to the brick and are therefore not available for inclusion in the grass region extracted subsequently. In a multiple feature environment, one would expect grass and brick to contrast strongly as they do in both the red and blue bands. Nonetheless, the importance of order must be recognized when using overlapping slice ranges.

5. Conclusion

The Ohlander algorithm attempts to overcome the uncertainties of image slicing by making available many images (and their histograms). This increases the likelihood that a region will appear homogeneous, yet will contrast with its surround, so that slicing is effective. The Superslice algorithm considers each sliced region individually and provides criteria for its acceptance. This allows slicing artifacts to be rejected and also provides a figure of merit for well-definedness. The Hyperslice algorithm is an attempt to combine these orthogonal points of view.

References

1. R. Ohlander, Analysis of Natural Scenes, Ph.D. Thesis, Carnegie-Mellon University, Pittsburgh, PA, December 1976.

2. D. L. Milgram, M. Herman, Clustering edge values for threshold selection, University of Maryland Computer Science Center, Technical Report 617, December 1977.

3. D. L. Milgram, Region extraction using convergent evidence, Proceedings: ARPA Image Understanding Workshop, April 1977, pp. 58-64.

4. D. L. Milgram, Progress report on segmentation using convergent evidence, Proceedings: ARPA Image Understanding Workshop, October 1977, pp. 104-108.

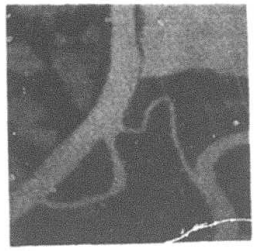


Fig. 1a

Fig. 1b

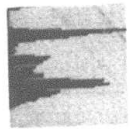


Fig. 1c

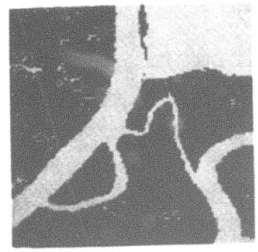
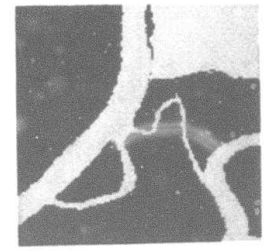


Fig. 1d



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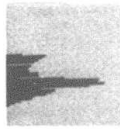

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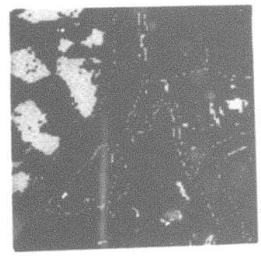

Fig. 1g

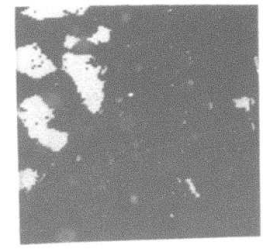

Fig. 1h

Fig. 1i

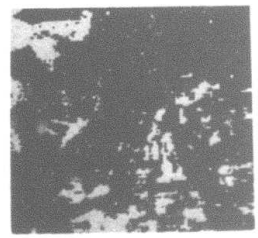

Fig. 1j

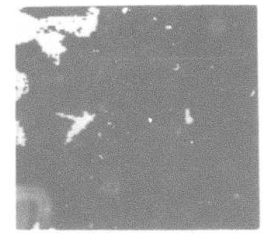

Fig. 1k

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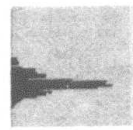


Fig. 1ℓ

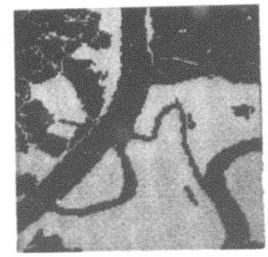


Fig. 1m

Figure 1. Recursive region extraction - Monterey image.

a. ERTS window.
b. Edge map.
c. Histogram of a., with selected slice range indicated.
d. Mask of slice range. Within range points are white.
e. ERM—extracted regions mask.
f. Histogram of available points after deleting extracted regions.
g. Slice range mask.
h. ERM.
i. Histogram of new APM.
j. Slice range mask.
k. ERM.
ℓ. Histogram of remaining points.
m. Mask of remaining points.

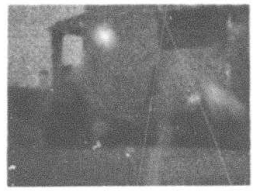
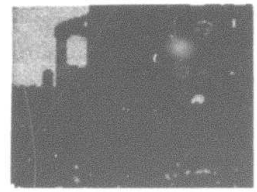


Fig. 2a

Fig. 2b

Fig. 2c



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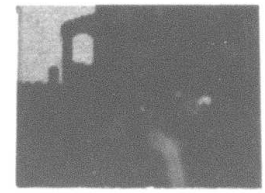
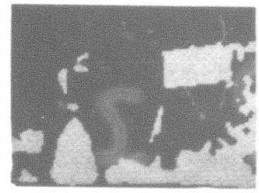


Fig. 2e

Fig. 2f



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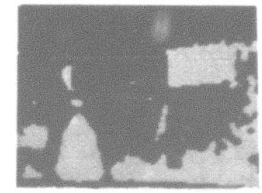
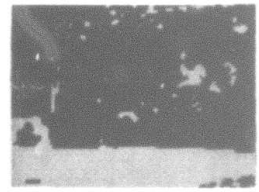


Fig. 2h

Fig. 2i



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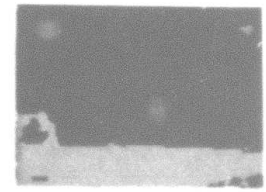

Fig. 2k

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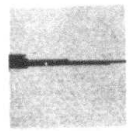

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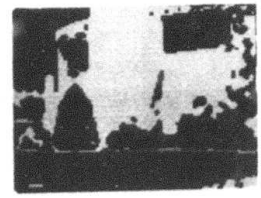

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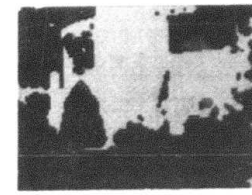

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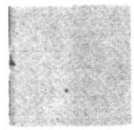

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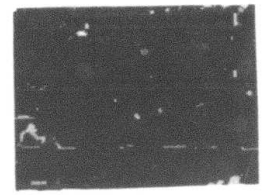
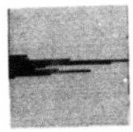


Fig. 2p

Figure 2. Recursive region extraction - house image.

a. House window - median filtered average of red, green and blue windows.
b. Edge map.
c.,f.,i.,ℓ. Histograms of successive APM's with slice ranges indicated.
d.,g.,j.,m. Slice range masks.
e.,h.,k.,n. Successive ERM's.
o. Histogram of remaining points.
p. Mask of remaining points.



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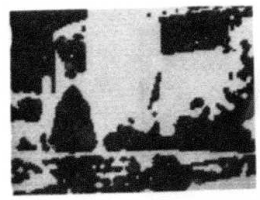


Fig. 3b

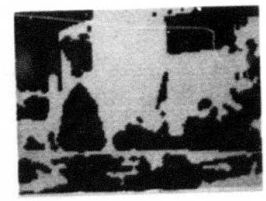
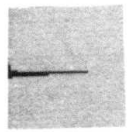


Fig. 3c



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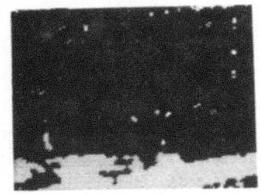

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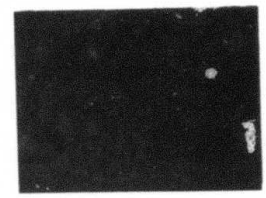
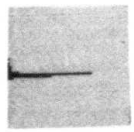


Fig. 3f



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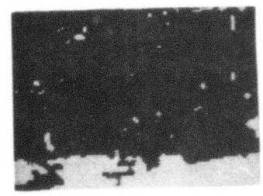

Fig. 3h

Figure 3. Effect of reordering slice-ranges.

a. Histogram as in Fig. 2i. with slice range as in Fig. 2ℓ.
b,e. Slice range masks.
c,f. Successive ERM's.
d. Resulting histogram with slice range as in Fig. 2i.
g. Resulting histogram.
h. Mask of remaining points.

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